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Impact of socioeconomic differences on distributional cost-effectiveness analysis

Running head: how socioeconomic differences affect DCEA

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Abstract

Public health decision makers value interventions for their impacts on overall health and health inequality. Distributional cost-effectiveness analysis (DCEA) incorporates health inequality concerns into economic evaluation by accounting for how parameters, such as effectiveness, differ across population groups. Good understanding of how and when accounting for socioeconomic differences between groups affects the assessment of intervention impacts on overall health and health inequality could inform decision makers where DCEA would add most value.

We interrogated two DCEA models of smoking and alcohol policies, using first national level and then Local Authority level information on various socioeconomic differences in health and intervention use. Through a series of scenario analyses, we explored the impact of altering these differences on the DCEA results.

When all available evidence on socioeconomic differences was incorporated, provision of a smoking cessation service was estimated to increase overall health and increase health inequality, while the screening and brief intervention for alcohol misuse was estimated to increase overall health and reduce inequality. Ignoring all or some socioeconomic differences resulted in minimal change to the estimated impact on overall health in both models, however, there were larger effects on the estimated impact on health inequality. Across the models there were no clear patterns in how the extent and direction of socioeconomic differences in the inputs translated into the estimated impact on health inequality. Modifying use or coverage of either intervention so that each population group matched the highest level improved the impacts to a greater degree than modifying intervention effectiveness. When local level socioeconomic differences were considered, the magnitude of impacts was altered; in some cases, the direction of impact on inequality was also altered.

Keywords

Distributional cost-effectiveness analysis, economic evaluation, health inequality, public health

Introduction

Cost-effectiveness analysis (CEA) is routinely employed to inform health care resource allocation decisions [1]. When allocating resources in public health, decision makers often consider how potential policies would improve population health and reduce unfair health inequalities (i.e., reduce the perceived unfairness of the distribution of health across the population) [2, 3]. The decision about whether to fund a public health intervention is therefore informed by its impact on the distribution of health across the population: both in terms of its sum total and the extent of inequality between relevant population groups. The distributional cost-effectiveness analysis (DCEA) framework considers how interventions impact the distribution of health [4, 5]. It is used to estimate the net impact of an intervention on overall health and in each population group of interest, and to examine the trade-offs between improving overall health and reducing health inequality.

To perform DCEA, the evaluation of costs and consequences of alternative interventions must account for differences between equity relevant groups [6]. This requires evidence on how the parameters of the evaluation, e.g., the value of inputs to a decision analytic model, vary between groups. Lack of evidence on between-group differences can make it challenging to conduct a formal evaluation. Even when the evidence is available, a DCEA is more complex than a standard CEA and policy makers may lack the resources to undertake DCEA in all circumstances. Developing greater understanding of how and when accounting for socioeconomic differences in model inputs affects the final estimate of the intervention impact on the distribution of health could enable us to identify a subset of parameters that are sufficient to inform the intervention impact, which may make it possible to simplify the DCEA process, and help decision makers and analysts to know where DCEA would add most and when to gather further evidence on socioeconomic differences.

When appraising how an intervention impacts on health inequality, a common question is whether anything can be done to modify either the intervention itself or the way in which it is delivered in order to make it benefit population groups more fairly [7]. For example, if uptake of the intervention is socially patterned, policy makers may ask whether it is worthwhile investing in actions that increase uptake in lower socioeconomic groups. A breakdown showing how eliminating socioeconomic differences in each model input could alter the final distribution of health could help direct efforts to answer such questions.

In the UK, Local Authorities have the responsibility of making decisions about which public health interventions to fund for their local population. However, many appraisals of the potential interventions are performed and reported at a national level [8]. The extent of socioeconomic differences in model inputs can vary between settings, e.g., the smoking prevalence by socioeconomic status within Local Authorities differs from the overall national figure [9]. The population distribution between socioeconomic groups may also differ between settings. Consequently, evaluating the intervention impact based on national level estimates may not be informative for the impact that would be expected at a local level. Therefore, it may be relevant to local decision makers to understand how local level variation will alter estimated policy impacts compared to the national level estimates.

In this study, we adapted two existing DCEA models of public health interventions to address four broad questions:
(a) how influential is failing to consider specific socioeconomic differences on the estimated intervention impacts on overall health and health inequality?;
(b) which modifiable intervention characteristics represent the most valuable targets to mitigate socioeconomic differences in intervention impact?;
(c) how generalisable are conclusions about the intervention impacts on overall health and health inequality between areas with different characteristics?;
(d) what conclusions can we draw about the generalisability of the results of the two studies to other interventions or disease areas?

Methods

Overview

DCEA of smoking and alcohol policies were conducted using two existing models [10, 11]. Health benefits were expressed as quality-adjusted life years (QALYs) and costs in pounds sterling (£, 2018 price year) under a National Health Service (NHS) and personal social services perspective. An annual discount rate of 3.5% was applied to both benefits and costs in accordance with National Institute for Health and Care Excellence (NICE) guidance [12]. The NICE cost-effectiveness threshold of £20,000 per QALY was used [13].

In both models, we considered inequality between population groups defined according to the level of socioeconomic deprivation in individuals' area of residence, i.e., Index of Multiple Deprivation (IMD) [14]. IMD is an area-level weighted composite index combining information on income, employment, health, education, housing, crime and living environment for a geographical area of approximately 1,500 residents [14]. As IMD is not an individual-level measure, there will be variation in the socioeconomic status of residents within each area and even highly deprived areas will have some high socioeconomic status inhabitants. The population was divided into five groups defined by quintile of IMD, and differences in model inputs across IMD quintiles were characterised. Both models estimate the amount by which policies change health within each population group. Summing over the change in health across all five groups gives the total change in population health, expressed as population incremental net health benefit (NHB) [1].

Considering the general population's preference for reducing health inequality between rich and poor groups, we can present the total population health as the 'equally distributed equivalent (EDE) health'. To calculate this EDE health, the strength of preference for reducing inequality is used as a weight to provide a weighted total population health. EDE health can be interpreted as the amount of health distributed equally to all population groups that would be considered equally valuable to the distribution being evaluated [4]. Given the preference for reducing existing health inequalities, the EDE is lower than the population health, and the difference describes the amount of overall health that people would be willing to sacrifice to achieve an equal distribution. Alternatively, the difference between the EDE and the total population health can be interpreted as the welfare cost of health inequality, as it represents the social value that could be gained if health were redistributed equally. A policy that leaves the total population health unchanged but reduces the difference in health between population groups will increase the EDE health. We expressed the policy impact on health inequality using the difference between how policies alter the EDE health (which increases with total health and with reduction of inequality in health) and how policies alter total health (incremental NHB).

Scenario analyses were performed to explore how altering socioeconomic differences in model inputs affects the estimated impacts.

Models

The smoking model is a cohort Markov model that assesses the cost-effectiveness of nicotine replacement therapies in adult smokers (18-75 years) over a lifetime horizon [10]. These therapies are accessed through primary care [10]. The Markov model includes three mutually exclusive health states: smokers, former smokers and death. Smokers and former smokers differ in mortality risk, health-related quality of life (HRQoL) and risk of developing six smoking-related diseases, modelled as events with impact on costs and HRQoL. The Sheffield Alcohol Policy Model is a hybrid simulation consisting of two linked models that evaluates the cost-effectiveness of screening and brief interventions (SBIs) to reduce alcohol misuse [11]. The first part of the model takes a baseline population of individual drinkers and simulates receipt of SBIs and the resulting age-adjusted trends in alcohol consumption over a 20-year time horizon. The second part of the model aggregates these individuals into cohorts based on age, gender, IMD quintile and baseline drinking level. The model simulates 45 alcohol-related health conditions, which are linked to associated mortality rates and hospital admissions.

In this study, we focus on the provision of e-cigarette in the smoking model and the strategy of delivering SBIs to all patients when registering with a new primary care practice ('Next Registration') in the alcohol model, both compared to 'no intervention'.

Impact on overall health

The models estimate the incremental direct health benefits and incremental healthcare costs of the interventions, compared to 'no intervention', specific to smokers and alcohol users in each IMD quintile. Zero health benefit accrues to people who are not eligible for the interventions (i.e. non-smokers and those who do not misuse alcohol). The incremental costs are converted into health opportunity costs, i.e., the health that would have been achieved if those resources had been used for other purposes, using the NICE cost-effectiveness threshold. The health benefits of making resources available for other purposes will not fall equally to all socioeconomic groups. Research has shown that a greater proportion of the benefit from changes in NHS spending goes to more deprived groups. Deprived groups therefore lose out most when resources are appropriated for specific policies, or conversely stand to gain the most when policies are cost saving and release resources [15]. For each IMD quintile, the health opportunity costs are subtracted from the direct health benefits to provide the distribution of the incremental net health benefit (iNHB), i.e. the change in health by population group. The impact on overall health is the population iNHB, i.e., the sum of iNHB across all quintiles.

Impact on health inequality

The baseline distribution of health is the distribution of quality-adjusted life expectancy (QALE) [16], which combines differences in life expectancy between groups with differences in quality of life between groups. The iNHB in each IMD quintile estimated for each intervention is added to the baseline QALE in each IMD quintile to estimate the predicted distribution of QALE following the implementation of the intervention. The QALE distribution is summarised as EDE health by using the Atkinson index, with an inequality aversion parameter derived from a UK population survey [17]. The Atkinson inequality aversion parameter describes the strength of preference for reducing relative inequality in health. When applied to calculate the EDE, it assigns higher weight to health improvements in more deprived groups that have lower baseline QALE, and a lower weight to health improvements in less deprived groups with greater baseline QALE [18]. The change from the EDE in the baseline health to the EDE of the health with the intervention, i.e., incremental EDE (iEDE), encompasses the impact of the intervention on both overall health and health inequality. To isolate the impact on health inequality, we look at the difference between iEDE and iNHB, with positive value showing that the intervention reduces the cost of health inequality. We illustrate these calculations for the smoking model in **Box 1**.

Box 1. Smoking cessation model

1. Extract the incremental direct health benefits (*a*) and the incremental healthcare costs (*b*) of e-cigarette vs 'no intervention' from the smoking DCEA model for each IMD quintile in England.

2. Sum the incremental costs (*c*) and then convert to health opportunity costs at a rate of £20,000 per QALY (*d*), i.e., £ (-156,391,946)/£20,000 = -7,820 QALYs.

3. Use the proportion of the health opportunity costs borne by each IMD quintile (*e*) to calculate the size of the health opportunity costs in each IMD quintile (*f*), e.g., health opportunity costs for IMD1 is -7,820*0.26 = -2,033 QALYs.

4. Calculate the incremental NHB for each IMD quintile (*g*) by subtracting health opportunity costs from the incremental direct health benefits, e.g., incremental NHB for IMD1 is 6,560 - (-2,033) = 8,593 QALYs.

5. Calculate the incremental NHB per capita by IMD quintile (*i*) using the distribution of the adult population of England (*h*), e.g., IMD1, the individual incremental NHB is 8,593/8,307,456 = 0.0010 QALYs.

6. Add the individual incremental NHB to the baseline QALE (*j*) to calculate the QALE with the intervention by IMD quintile (*k*).

7. Calculate EDE for the baseline QALE distribution (*l*) and the QALE distribution with the intervention (*m*) using the Atkinson social welfare function with an inequality aversion parameter, ε, of 10.95.

$$EDE = \left(\frac{1}{N}\sum h_i^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}$$

h_i= individual QALE for a person in IMD quintile i
N= total population size
ε= Atkinson inequality aversion parameter

8. Calculate the population incremental EDE with the intervention (*n*), i.e., the difference of population EDE with the intervention and the population baseline EDE, where the population EDE is multiplying EDE by total population size.

9. Calculate the population incremental NHB with the intervention (*o*), i.e., sum incremental NHB across all quintiles.

10. Calculate how the intervention changes health inequality (iEDE-iNHB) (*p*), i.e., 70,002 - 80,782 = -10,780 QALYs.

		IMD1 (most deprived)	IMD2	IMD3	IMD4	IMD5 (least deprived)
1.	**(a) Incremental direct health benefits[1],QALYs**	6,560	15,619	13,201	19,350	18,233
	(b) Incremental costs[1], £	-12,544,948	-32,507,825	-29,016,052	-42,924,171	-39,398,949
2.	**(c) Total incremental costs (sum of b), £**			-156,391,946		
	(d) Total health opportunity costs (c/20,000), QALYs			-7,820		
3.	**(e) Proportion of health opportunity costs[2]**	0.26	0.22	0.22	0.16	0.14
	(f) Health opportunity costs (d*e), QALYs	-2,033	-1,720	-1,720	-1,251	-1,095
4.	**(g) Incremental NHB (a-f), QALYs**	8,593	17,339	14,921	20,601	19,328
5.	**(h) Population size[3]**	8,307,456	8,863,275	8,790,681	8,657,257	8,376,275
	(i) Individual incremental NHB (g/h), QALYs	0.0010	0.0020	0.0017	0.0024	0.0023
6.	**(j) Baseline QALE (no intervention)[4]**	64.7	68.5	70.6	73.6	75.6
	(k) QALE with e-cigarette (i+j)	64.7010	68.5020	70.6018	73.6024	75.6023
7.	**(l) Baseline EDE, QALYs**			69.465		
8.	**(m) EDE with the intervention, QALYs**			69.467		
	(n) Population incremental EDE (m*sum of h-l*sum of h), QALYs			70,002		
9.	**(o) Impact on overall health (sum of g)**			80,782		
10.	**(p) Impact on health inequality (n-o)**			-10,780		

[1]calculated using results from the model.
[2]Love-Koh J et al. Estimating Social Variation in the Health Effects of Changes in Healthcare Expenditure. *Medical Decision Making* 2020.
[3]Office for National Statistics (ONS) mid-year population estimates 2017.
[4]Love-Koh J et al. The Social Distribution of Health: Estimating Quality-Adjusted Life Expectancy in England. *Value in Health* 2015.

Inequality in model inputs

Model inputs in which we reflect socioeconomic differences were categorised into four groups: background parameters, behaviours, health consequences of behaviour, and intervention characteristics. The level and direction of inequality in these model inputs between population groups are summarised using the concentration index [19] (**Table 1**). It ranges from -1 to 1, with negative values demonstrating higher values of the input in more deprived groups, while positive values demonstrate higher values in less deprived groups. The following sections give an overview of each category of input, and more detailed information is available in the **Appendix**.

Background parameters

Background parameters reflect the level of health that would be observed without interventions, including the baseline QALE [16] and health opportunity costs [15]. Baseline QALE is higher in less deprived areas and more health opportunity costs fall on residents in more deprived areas (**Table 1**).

Behaviours

Behaviours including the smoking prevalence and the abstention from drinking by IMD quintile were based on survey data. The smoking model incorporated the proportion of smokers in each IMD quintile [9]. The alcohol model incorporated socioeconomic differences in abstention from drinking, average weekly consumption and peak day drinking. People in more deprived groups are more likely to smoke but less likely to drink, drink less on average and 'binge' drink at lower levels (**Table 1**).

Health consequences of behaviour

Health consequences of behaviour include mortality, related diseases and HRQoL. In the smoking model, the annual mortality rates for smokers (**Figure S1**) were based on general population all-cause mortality [20], proportion of smokers, former smokers and non-smokers [21], and the increased relative risk of death for smokers [22]. Mortality in the alcohol model was modelled separately by health condition, including alcohol-related mortality and all other causes combined (**Figure S2**). In both models, there is a higher death rate in more deprived areas (**Table 1**).

The socioeconomic difference in the smoking-related diseases was estimated using the average population incidence [21] and the relative risk between IMD quintiles of developing smoking-related disease [23]. We assumed that the middle IMD quintile, i.e., IMD3, was represented by the average incidence of smoking-related disease, and then applied relative risks to estimate incidence in other IMD quintiles. Data on alcohol-related diseases were obtained from individual hospital records. People living in more deprived areas are more likely to develop smoking- and alcohol-related diseases (**Table 1**).

The smoking model included HRQoL for smokers and former smokers by IMD quintile, estimated from survey data by linear regression (details available in **Table S6**). People living in less deprived areas tend to have higher HRQoL (**Table 1**). The same decrement in HRQoL for each smoking-related disease was applied across all IMD quintiles as no evidence was identified to inform differential effects. In the alcohol model, separate HRQoL values were applied for each alcohol-related health condition for each age-sex subgroup [24], with no evidence available for differences by IMD quintile.

In both models, the healthcare costs associated with disease-related events are not differentiated by IMD, as we did not identify evidence that would let us impose a different healthcare costs per health event by deprivation.

Intervention characteristics

Socioeconomic differences in intervention impact were incorporated in both models. In the smoking model, the socioeconomic difference in effectiveness (**Table S7**) was incorporated assuming that the middle quintile was represented by the average quit rate for the intervention [25], and then applying the relative risk of quitting between IMD quintiles [26]. The socioeconomic difference in intervention uptake was based on the proportion of smokers supplied with an NHS Stop Smoking Service [21]. In the alcohol model, we did not consider socioeconomic difference in the intervention effect because of the lack of clear evidence, but incorporated the difference in the access to the intervention. It consists of an initial step where individuals attending primary care are selected to be screened, informed by the rates at which individuals register with new GP practices [27] (**Table S8**) and a second step where those identified as drinking at potentially risky levels (screen positive) receive an intervention, estimated using the Alcohol Toolkit Study [28] (**Table S9**). The concentration indices show higher effectiveness and uptake of smoking cessation in less deprived areas, while those for alcohol interventions show higher screening coverage and screening positive in more deprived areas (**Table 1**).

Local Authority level inputs

To contrast national level results to local area results, we selected two Local Authorities with distinct socioeconomic profiles (smoking: **York** and **Sheffield**; alcohol: **Liverpool** and **Trafford**). More residents in York and Trafford live in the least deprived quintile compared to England as a whole, while in Sheffield and Liverpool more residents living in the most deprived quintile (**Figures S3 & S4**) [29]. The smoking model used local information on smoking prevalence only (**Figure S5**), while the alcohol model included local information on mortality and morbidity rates from alcohol-related diseases, the abstention of drinking and mean weekly alcohol consumption (**Figure S6**). The remaining differences for other parameters were based on national level figures in the absence of relevant data.

Analysis

A series of scenario analyses were performed to explore the impact of altering the socioeconomic differences in model inputs on DCEA results, corresponding to the four questions raised in introduction. The intervention impacts estimated in each scenario analysis were compared to the 'base case' estimates, which constitute the results when all the socioeconomic differences in the model inputs mentioned previously are incorporated. We assume that the 'base case' represent the 'best' estimate of the intervention impacts. The 'base case' results and the results of each scenario analysis are presented as scatter plots on the health equity impact plane [3]. The differences from the 'base case' reflect in which direction and to what extent each scenario affects how well the each model estimates intervention impact on the distribution of health.

Question (a): all model inputs were set to the population average value in all IMD quintiles. This is equivalent to a standard CEA in which only the average population impact on overall health is calculated. It was expected that ignoring all socioeconomic differences would have minimal effect on the estimated impact on overall health but a larger effect on the impact on health inequality. We then excluded socioeconomic difference in one model input at a time and compared the model outputs with the 'base case' estimates. This illustrates to what degree ignoring socioeconomic difference in each model input would affect the estimates of impacts on overall health and health inequality.

Question (b): the model inputs we identified as potentially modifiable intervention characteristics were set to the highest level achieved in any of the groups to explore the value of ‘levelling up’ to eliminate the differences. In the smoking model, all groups were assumed to have the highest probability of quitting smoking and highest intervention uptake rate. In the alcohol model, the alcohol misuse screening coverage was assumed to go up to the highest level across all quintiles within the same age-sex group (‘age-sex max’) and also the highest across all age-sex-deprivation groups (‘global max’).

Question (c): the model inputs reflecting socioeconomic differences at local level were incorporated to estimate the ‘base case’ results for two Local Authorities in each model. To enable comparisons across areas that differ in population size, the intervention impacts for 100,000 adults were presented. The ‘base case’ results at local level were compared between Local Authorities and to the results for the nation as a whole.

Question (d): as the two models evaluated different interventions in different disease areas, we compared the results of abovementioned analyses in the two models to assess how the conclusions might vary between models. Additionally, for analyses in addressing question (a), we rearranged the results by plotting the changes in the estimated impacts against the concentration index of the model input which was ignored and then compared these across both models to explore the possible patterns between the extent of inequality of model inputs and the variations in estimated impacts on overall health and health inequality.

Results

The results of base case and scenario analyses are summarised in **Table 2** and plotted in **Figure 1** and **Figure 2**. These base case estimates indicate that compared to ‘no intervention’, e-cigarette was estimated to increase overall health (iNHB=80,782 QALYs), but increase health inequality (iEDE-iNHB=-10,780 QALYs), while the alcohol ‘Next Registration’ strategy was estimated to increase overall health (iNHB=4,336 QALYs) and reduce inequality (iEDE-iNHB=444 QALYs) (**Table 2**).

(a) How influential is failing to consider socioeconomic differences?

Ignoring socioeconomic differences in all model inputs

Compared to the base case, ignoring socioeconomic differences in all model inputs reduced the amount by which the interventions were predicted to increase overall health (smoking model: -272 QALYs, -0.34%; alcohol model: -253 QALYs, -5.83%) (**Table 2**); e-cigarette was predicted to have no effect on inequality and the alcohol 'Next Registration' strategy was predicted to increase inequality (**Table 2** & **Figure 1**).

Ignoring the socioeconomic difference in one model input at a time

Compared to the base case, in the smoking model, ignoring the socioeconomic difference in smoking prevalence resulted in the greatest increase in the estimated overall health impact (4,902 QALYs, 6.07% greater than the total in base case), while ignoring the difference in intervention effectiveness resulted in the greatest reduction (-3,564 QALYs, -4.39%) (**Table 2**). In the alcohol model, ignoring the socioeconomic difference in mean alcohol consumption resulted in the greatest increase in the estimated overall health impact (756 QALYs, 17.44%), while ignoring the difference in drinking prevalence resulted in the greatest reduction (-389 QALYs, -8.97%) (**Table 2**).

In the smoking model, ignoring the socioeconomic differences in health opportunity costs, smoking prevalence and risk of smoking-related diseases increased the extent by which the intervention was estimated to increase inequality, while ignoring socioeconomic differences in baseline QALE, mortality risks, HRQoL, effectiveness and uptake reduced this extent (with removal of the socioeconomic difference in uptake making e-cigarette inequality-reducing), compared to the base case (**Figure 1a**). In the alcohol model, ignoring the socioeconomic differences in average weekly consumption, peak day consumption, screening coverage, likelihood of screening positive and the health opportunity costs increased the extent by which the intervention was estimated to reduce inequality, while ignoring the socioeconomic differences in abstention from drinking, alcohol-related diseases and mortality rates reduced it (with removal of the socioeconomic difference in morbidity making the strategy inequality-increasing) (**Figure 1b**).

(b) Which modifiable intervention characteristics represent the most value?

Levelling up effectiveness and uptake of smoking cessation intervention increased the estimated overall health impact by 7,448 QALYs (9.22%) and 28,875 QALYs (35.74%), respectively, and reduced the extent by which it was predicted to increase inequality, with levelling up uptake making e-cigarette inequality-reducing, compared to the base case (**Table 2** & **Figure 2a**).

In the alcohol model, increasing coverage of the 'Next Registration' strategy to the age-sex specific maximum level increased the estimated improvement in overall health by 480 QALYs (11.07%) and increased the extent by which it was estimated to reduce inequality, and increasing the coverage to population maximum level increased the estimated improvement in overall health by 13,556 QALYs (312.64%) and reduced health inequality to a much greater extent (**Table 2** & **Figure 2b**).

(c) How generalisable are conclusions between settings?

Results per 100,000 adults for each setting are presented in **Figure 3**. In the smoking model, using local level evidence, e-cigarette was estimated to improve overall health in England, York and Sheffield with different magnitudes of impacts (**Figure 3a**); it was estimated to increase inequality in Sheffield and England but reduce inequality in York (**Figure 3a**). The alcohol 'Next Registration' strategy was estimated to increase overall health and reduce inequality in England and both Local Authorities, but the greatest increase in overall health was in Liverpool and the greatest reduction in health inequality was in Trafford (**Figure 3b**).

(d) How generalisable are the results between models and disease areas?

The concentration index of each model input and the amount by which ignoring it alters the estimated intervention impacts on overall health and health inequality is plotted in **Figure S7** and **Figure 4**, respectively. In both models, there was no clear pattern relating inequality of the model input to how it alters the estimated impact on overall health (**Figure S7**). In the smoking model, there was a positive correlation between the concentration index and the impact of ignoring socioeconomic differences in that input on the estimated health inequality impact, compared to the base case (**Figure 4a**). Ignoring the socioeconomic differences in model inputs that are more concentrated on the less deprived (positive concentration index values) increases the amount by which the intervention is estimated to reduce inequality while ignoring the socioeconomic differences in model inputs concentrated on the more deprived results (negative concentration index values) decreases it. However, this pattern was not clearly observed in the alcohol model (**Figure 4b**).

Discussion

Evidence on how the impacts of policies vary across population groups is vital to inform decisions that rest on consideration of impacts on overall health and health inequality. By interrogating two different DCEA models that feature opposite effects on inequality, we demonstrated how the evidence for socioeconomic differences in policy impact could be evaluated within a DCEA framework, which represents a form of stratified cost-effectiveness analysis. Good understanding of how and when accounting for socioeconomic differences between groups affects the assessment of intervention impacts on overall health and health inequality could advice researchers whether it is possible to simplify the DCEA process and inform decision makers where DCEA would add most value.

First, we found that failing to consider socioeconomic differences would affect the estimated policy impacts to a different degree between the two models. It has a more minor influence on the estimated overall health impact in the smoking model, and a greater influence in the non-linear alcohol model (smoking model: -0.21% alcohol model: -5.83%). As anticipated, it greatly affected the estimated impact on health inequality, influencing not only the magnitude but also the direction of effect (smoking: increase inequality to no effect; alcohol: reduce inequality to increase inequality). Ignoring socioeconomic differences in just one input can have a substantial effect on the results, but we found no clear relationship that might predict which model inputs are most influential.

Second, levelling up modifiable intervention characteristics to the highest level achieved in any subgroup would improve estimated health inequality impact to the direction that favours the interventions. It also increases the estimated overall health impact, so it would not impose a trade-off between improvement in overall health and reduction in inequality. Socioeconomic variation in smoking cessation uptake appears a more valuable target for modification than socioeconomic variation in effectiveness. This could inform decision makers where to focus efforts to make policies benefit population groups more fairly. It should be noted that such efforts usually attract additional costs, and further analysis would be needed to explore whether the benefits are worthwhile.

Third, the magnitude of impacts on overall health and health inequality at one Local Authority was different compared to that at another Local Authority or the nation as a whole. In the smoking model, the direction of the impact was also different (e-cigarette was estimated to reduce inequality in York, but to increase inequality measured across England and Sheffield). The inconsistency in the policy impacts between settings is likely to be driven by the different deprivation structures of the populations and the local level socioeconomic differences. This suggests that caution should be taken when generalising recommendation of interventions from national level to Local Authorities, and between Local Authorities differing in deprivation structure of the population and other model inputs. Prioritisation and local level decision making could be better supported by conducting and reporting analyses that reflects differences relevant to the local context.

The conclusions that can be drawn from this study are limited as it is based on only two models. Although both decision models have been used to support real resource allocation decisions in the UK, the base case results may omit potential socioeconomic differences in inputs where evidence was not available. For example, if disease-related events require more resource use for treatment, or impose a greater quality of life decrement, in more deprived groups, the socioeconomic differences in healthcare costs and health-related quality of life would be underestimated. In view of this, sensitivity analyses of more DCEA models can be combined with the results from our analysis to further our understanding of how influential considering socioeconomic differences in different types of model input is on the estimated policy impacts. We have not considered alternative interventions or designs of the interventions (e.g. extra efforts on targeting disadvantaged groups), which would be expected to have alternative impacts on inequalities, but there is scope for the use of DCEA and other methods to help inform how best to design interventions to impact on inequalities. Additionally, the evidence on socioeconomic differences in model inputs is associated with uncertainty. The smoking model incorporated this uncertainty, which could be analysed with a probabilistic sensitivity analysis, to provide credible intervals around estimated policy impacts. However, the computing time for the individual simulation alcohol model was already high and did not allow for probabilistic sensitivity analysis. Consequently, we did not compare the influence of uncertainty across the two models.

The results presented in this study indicate that between-group differences in patterns of disease, intervention efficacy and intervention use can combine and interact in a complex manner and produce results that are difficult to predict. Thus, a formal analysis of inequality impacts, such as that provided by a full DCEA, can be beneficial in guiding resource allocation decisions. In practice, the decision on whether to conduct a DCEA or some other form of stratified analysis may be informed by qualitative approaches, similar to those used in the integrated health technology assessment (HTA) process [30]. A number of other methods have been proposed in the literature for including health inequality concerns in economic evaluation, for example the extended CEA [31], but these methods would rely on the same evidence on socioeconomic differences utilised here [5] and do not use inequality indices to explicitly analyse trade-offs between improving health and reducing health inequality. Although we have seen in this study that additional work is needed to conduct the DCEA and the approach would increase complexity and introduce uncertainty, the applications of DCEA have shown that it is feasible to implement within a typical HTA process and the skills required lie within the capabilities of analysts currently conducting CEA [4]. The trade-offs between health improvement and inequality reduction, informed by a full DCEA, would assist decision makers to clarify and quantify the nature of their inequality concerns and provide better ways of communicating findings to wider audiences [4].

Conclusions

By conducting two case studies, one assessing smoking cessation intervention and the other assessing alcohol screening and brief intervention, we found that conclusions about their impact on health inequality are strongly influenced by socioeconomic differences in model inputs, but not in an easy way to predict. This affirms the potential value for increasing the extent of formal and quantitative analysis of health inequality impacts to inform resource allocation decisions. Our study also suggests the need for better consideration of the diversity in deprivation structure, epidemiology and access to services across settings.

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Tables

Table 1. Category and concentration index of model inputs incorporating socioeconomic variation

Category:	**Gradient in:**	**Concentration index**
Background parameters (both models)	Baseline quality-adjusted life expectancy	0.03
	Health opportunity costs	-0.12
Behaviours	Smoking: prevalence	-0.08
	Alcohol: abstention from drinking	0.06
	Alcohol: average weekly consumption	0.03
	Alcohol: peak day consumption	0.06
Health consequences of behaviour	Smoking: mortality	-0.08
	Alcohol: mortality	-0.07
	Smoking-related diseases	-0.02
	Alcohol-related diseases	-0.05
	Smoking: health-related quality of life	0.01
Intervention characteristics	Smoking: intervention effectiveness (quit smoking)	0.04
	Smoking: intervention uptake	0.17
	Alcohol: individuals screened for alcohol misuse	-0.01
	Alcohol: probability of screening positive	-0.01

Table 2. Estimates of impacts on overall health and health inequality in base case and scenario analysis

		iNHB	Change in iNHB from base case	iEDE	Change in iEDE from base case	Inequality (iEDE-iNHB)	Change in the impact on inequality compared to base case
Smoking model (e-cigarette vs 'no intervention')							
Base case		80,782	-	70,002		-10,780	**Increase inequality**
(a) Ignoring all gradients		80,510	-272 (-0.34%)	80,510	10,508 (15.01%)	0	Smaller increase
(b) Ignoring gradient in:	Baseline QALE	80,782	0 (0%)	80,781	10,779 (15.40%)	-1	Smaller increase
	Health opportunity costs	80,782	0 (0%)	69,019	-983 (-1.40%)	-11,763	Larger increase
	Smoking prevalence	85,683	4,902 (6.07%)	69,454	-548 (-0.78%)	-16,229	Larger increase
	Mortality	79,543	-1,239 (-1.53%)	70,261	259 (0.37%)	-9,282	Smaller increase
	Smoking-related diseases	82,418	1,636 (2.03%)	70,853	851 (1.22%)	-11,564	Larger increase
	HRQoL	80,628	-153 (-0.19%)	70,053	51 (0.07%)	-10,575	Smaller increase
	Effectiveness	77,236	-3,546 (-4.39%)	69,942	-60 (-0.09%)	-7,294	Smaller increase
	Uptake	80,436	-345 (-0.43%)	81,463	11,461 (16.37%)	1,027	Inequality-reducing
(c) Levelling up to the best in:	Effectiveness	88,229	7,448 (9.22%)	79,929	9,927 (14.18%)	-8,300	Reduce
	Uptake	109,656	28,875 (35.74%)	111,057	41,055 (58.65%)	1,400	Inequality-reducing
Alcohol model ('**Next Registration' vs 'no intervention'**)							
Base case		4,336	-	4,780	-	444	**Reduce inequality**
(a) Ignoring all gradients		4,083	-253 (-5.83%)	3,580	-1,199 (-25.08%)	-503	Increases inequality
(b) Ignoring gradient in:	Baseline QALE	4,336	0 (0%)	4,336	-444 (-9.29%)	0	Smaller reduction
	Health opportunity costs	4,336	0 (0%)	4,989	209 (+4.37%)	652	Larger reduction
	Abstention	3,947	-389 (-8.97%)	4,125	-655 (-13.7%)	178	Smaller reduction
	Mortality	4,530	194 (+4.47%)	4,565	-215 (-4.5%)	35	Smaller reduction
	Alcohol-related diseases	4,856	519 (+11.97%)	4,645	-135 (-2.82%)	-211	Increases inequality
	Average weekly consumption	5,092	756 (+17.44%)	6,253	1,474 (+30.84%)	1,162	Larger reduction
	Peak day consumption	4,724	388 (+8.95%)	5,421	642 (+13.43%)	698	Larger reduction
	Screening coverage	4,493	157 (+3.62%)	5,492	713 (+14.92%)	999	Larger reduction
	Screening positive (risky level)	4,803	466 (+10.75%)	5,512	732 (+15.31%)	709	Larger reduction
(c) Levelling up to the best in:	Screening rates (age-sex max)	4,817	480 (+11.07%)	6,213	1433 (+29.98%)	1,397	Larger reduction
	Screening rates (global max)	17,893	13,556 (+312.64%)	22,141	17361 (+363.2%)	4,248	Larger reduction

QALE: quality-adjusted life expectancy
HRQoL: health-related quality of life
iNHB: incremental net health benefit
iEDE: incremental equally distributed equivalent health

Figures

Figure 1. Health equity impact plane* showing scenario analysis results where socioeconomic differences are ignored

Figure 1a. Smoking model

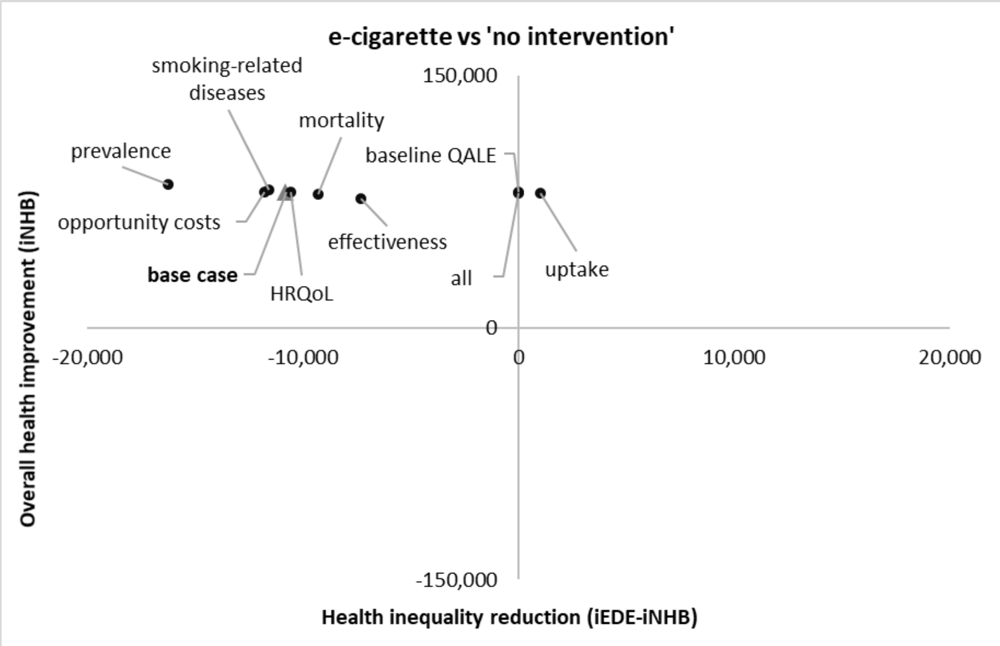
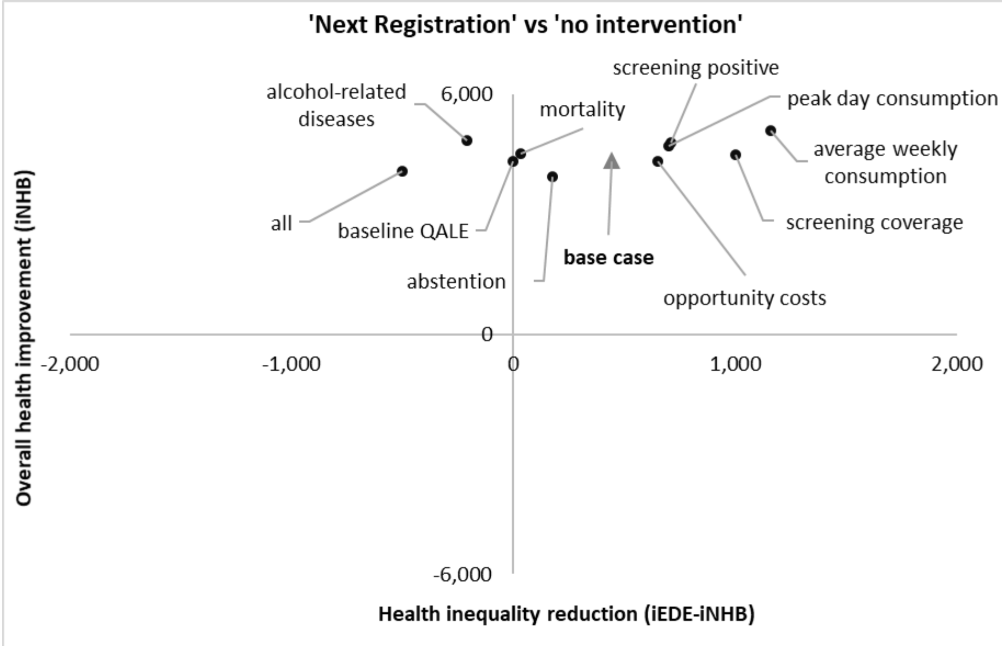


Figure 1b. Alcohol model



*In the health equity plane, the y axis is the increase in population health and the x axis is the reduction in health inequality. Interventions that improve overall health fall in the north of the plane. Interventions that reduce inequality fall in the east of the plane. E-cigarette was estimated to increase overall health and increase inequality, so it locates in the north-west quadrant. 'Next Registration' was estimated to increase overall health and reduce inequality, so it locates in the north-east quadrant.

Compared to the base case, if the location of the result in scenario analysis moves upward on the y axis, the model estimates more health improvement; if the location moves towards the right side on the x axis, the model estimates less inequality. For example, in the smoking model, the result of ignoring the socioeconomic difference in effectiveness moves downward and to the right, which indicates less health improvement and less inequality, compared to the base case.

Figure 2. Health equity impact plane* showing scenario analysis results where levelling up to the best

Figure 2a. Smoking model

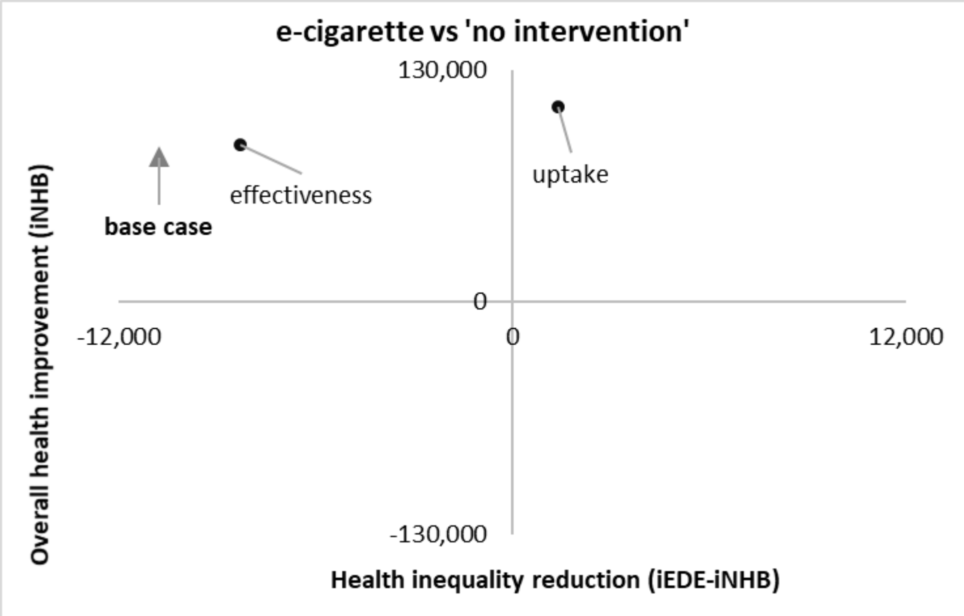
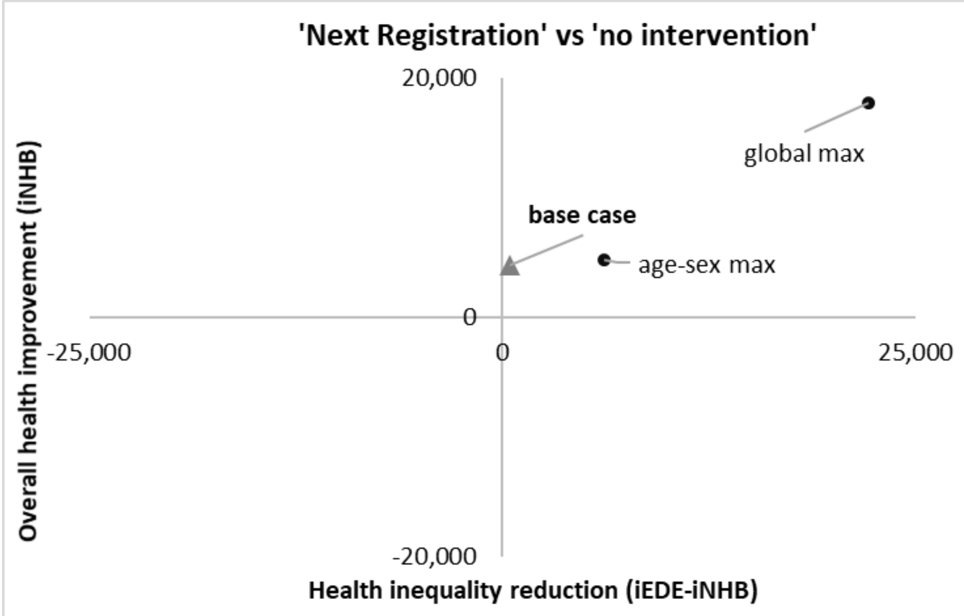


Figure 2b. Alcohol model



*Compared to the base case, if the location of the result in scenario analysis moves upward on the y axis, the model estimates more health improvement; if the location moves towards the right side on the x axis, the model estimates less inequality. For example, in the smoking model, the result of levelling up uptake moves upward and to the right, which indicates more health improvement and less inequality, compared to the base case. The location of 'uptake' is in the north-east quadrant, indicating the intervention is estimated to reduce inequality.

Figure 3. Equity impact plane* showing the overall health and health inequality for Local Authority analysis

Figure 3a. Smoking model

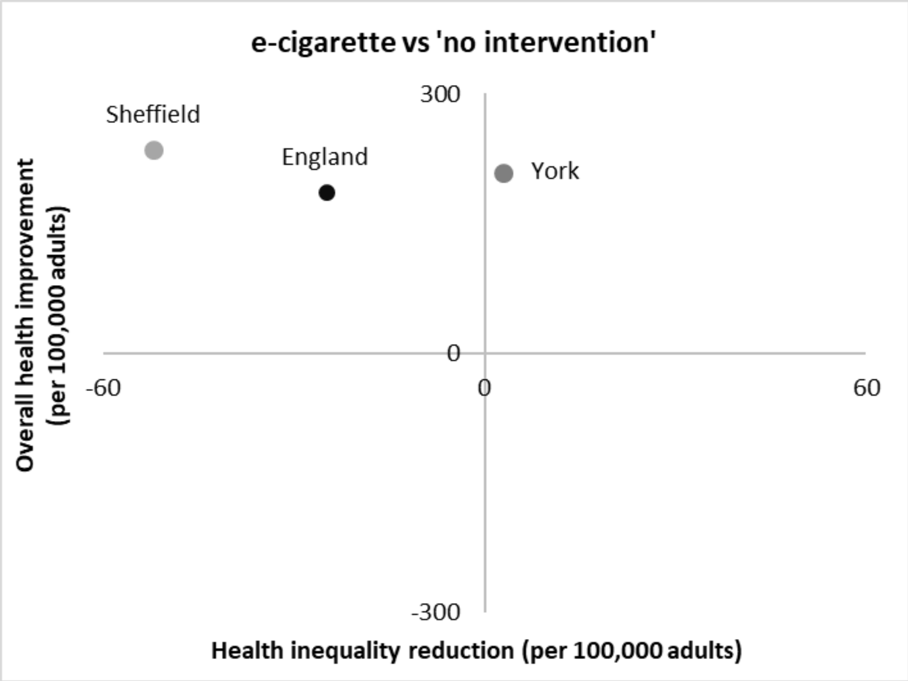
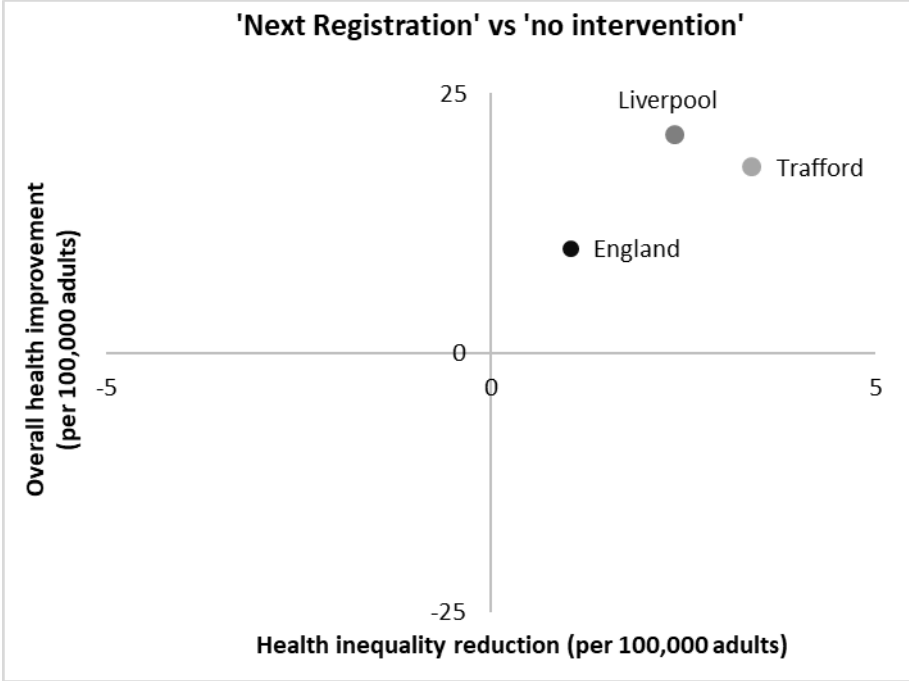


Figure 3b. Alcohol model



*Compared to the base case, if the location of the result in scenario analysis moves upward on the y axis, the model estimates more health improvement; if the location moves towards the right side on the x axis, the model estimates less inequality. For example, in the smoking model, the result for 'Sheffield' moves upward and to the left, which indicates more health improvement and more inequality, compared to the result for 'England'.

Figure 4. Impact on health inequality vs. concentration index where socioeconomic differences are ignored

Figure 4a. Smoking model

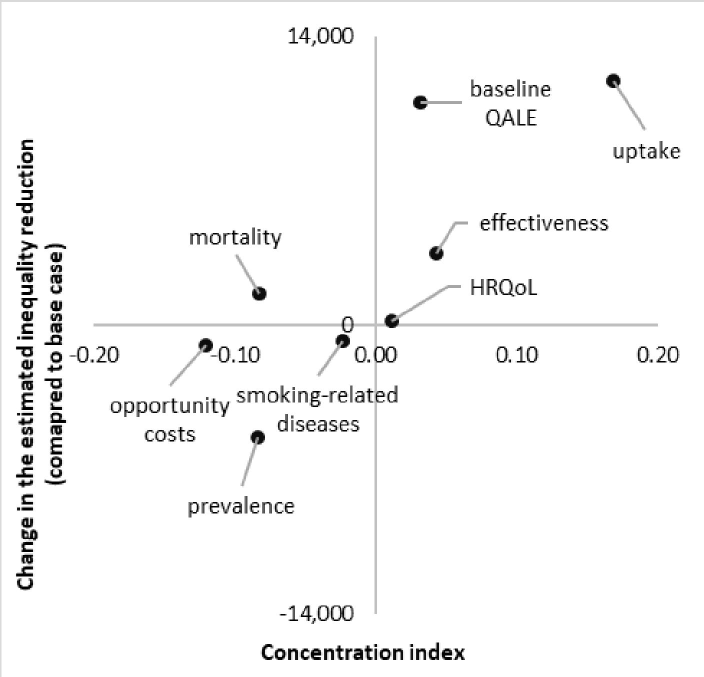
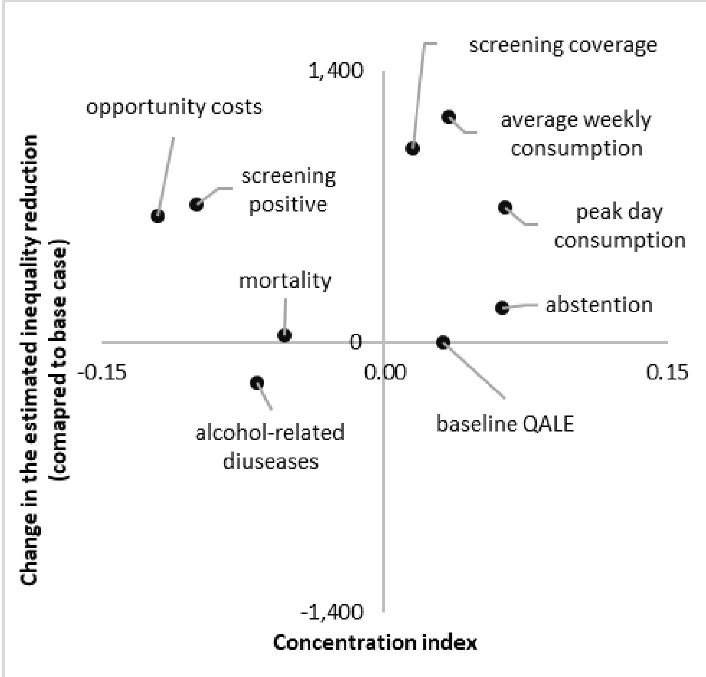


Figure 4b. Alcohol model



Appendices

Table S1. Distribution of health opportunity costs by IMD quintile groups

Parameter	Value	Source
IMD1 (most deprived)	0.26	Love-Koh et al. (2016) (1)
IMD2	0.22	
IMD3	0.22	
IMD4	0.16	
IMD5 (least deprived)	0.14	

IMD: Index of Multiple Deprivation

Table S2. Distribution of the adult population of England

	Adult population
IMD1 (most deprived)	8,307,456
IMD2	8,863,275
IMD3	8,790,681
IMD4	8,657257
IMD5 (least deprived)	8,376,275

IMD: Index of Multiple Deprivation

Table S3. The social distribution of baseline QALE in England

	QALE at birth (years)	Source
IMD1 (most deprived)	64.7	Love-Koh et al. (2015) (2)
IMD2	68.5	
IMD3	70.6	
IMD4	73.6	
IMD5 (least deprived)	75.6	

IMD: Index of Multiple Deprivation

QALE: quality-adjusted life expectancy

Table S4. Smoking prevalence by IMD in England (2017)

Smoking prevalence	Mean	95% confidence interval
IMD1 (most deprived)	17.17%	16.55%, 17.79%
IMD2	15.96%	15.22%, 16.70%
IMD3	14.09%	13.24%, 14.95%
IMD4	12.68%	11.80%, 13.57%
IMD5 (least deprived)	11.38%	10.53%, 12.24%

IMD: Index of Multiple Deprivation

Table S5. Socioeconomic differences in drinking

Deprivation quintile	Abstention rate	Average weekly consumption (units/drinker)	Peak day consumption (units/drinker)
IMD1 (most deprived)	28.2%	13.00	4.44
IMD2	32.0%	12.01	3.96
IMD3	14.1%	12.54	4.33
IMD4	12.3%	13.63	5.11
IMD5 (least deprived)	7.1%	14.95	5.71

IMD: Index of Multiple Deprivation

Table S6. Output from HRQoL regression model using EQ-5D data from the Health Survey for England 2012 and 2014

Variable		Coefficient	Standard error
Constant		0.903^{***}	0.0139
Age group	16-24	Ref	
	25-34	-0.0124^{***}	0.0137
	35-44	-0.0544^{***}	0.0133
	45-54	-0.0681^{***}	0.0135
	55-64	-0.0986^{***}	0.0138
	65-74	-0.107^{***}	0.0145
	75+	-0.1630^{***}	0.0165
Smoking status	Former smoker	Ref	
	Smoker	-0.0340^{***}	0.0069
IMD	IMD1 (most deprived)	Ref	
	IMD2	0.0320^{**}	0.0099
	IMD3	0.0281^{**}	0.0101
	IMD4	0.0545^{***}	0.0102
	IMD5 (least deprived)	0.0736^{***}	0.0101
Adjusted R-squared		**0.0414**	

$^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$
IMD: Index of Multiple Deprivation
HRQoL: health-related quality of life

Table S7. Relative risk of quitting smoking

Parameter	Value	95% confidence interval	Distribution	Source
IMD1 (most deprived)	1	-		Dobbie et al. 2015 (3)
IMD2	1.35	0.94, 1.81	Lognormal*	Grant 2014 (4)
IMD3	1.22	0.79, 1.73	Lognormal*	
IMD4	1.27	0.91, 1.67	Lognormal*	
IMD5 (least deprived)	1.36	0.94, 1.82	Lognormal*	

*Estimates transformed to the log scale
IMD: Index of Multiple Deprivation

Table S8. Socioeconomic difference in screening rates in the alcohol model

Deprivation quintile	'Next Registration' strategy	Source
IMD1 (most deprived)	9.4%	Weir et al. 2017 (5)
IMD2	12.6%	
IMD3	12.8%	
IMD4	11.2%	
IMD5 (least deprived)	11.1%	

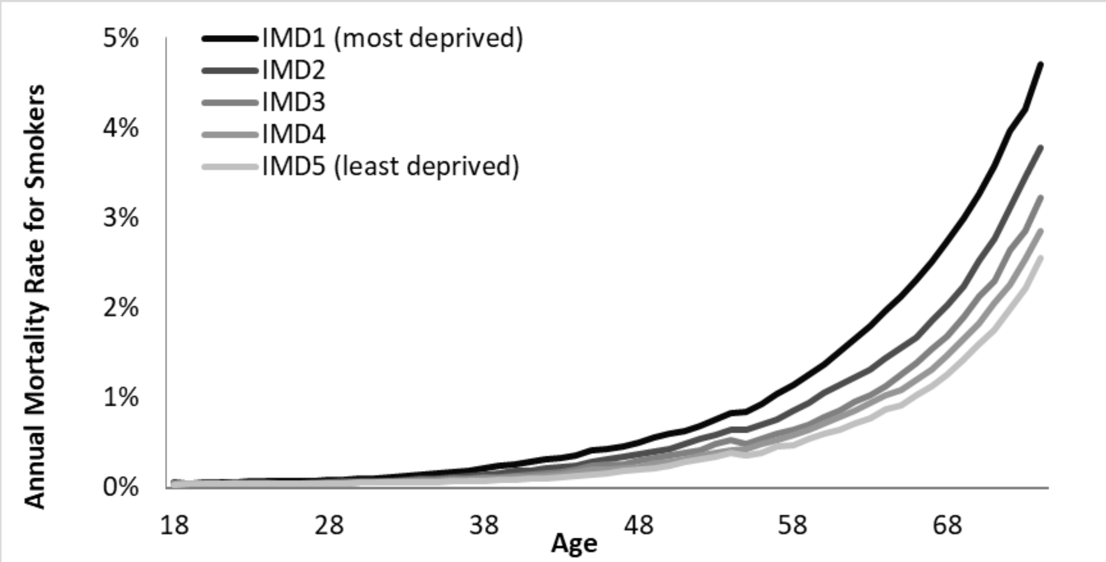
IMD: Index of Multiple Deprivation

Table S9. Output from screening outcome regression model in the alcohol model from Alcohol Toolkit Study

Variable		**Odds Ratio**	**Standard Error**
Constant		0.1226***	0.0055
Age group	16-24	Ref	
	25-34	0.4944***	0.0216
	35-54	0.2655***	0.0105
	55+	0.0750***	0.0035
Sex	Male	Ref	
	Female	0.7267***	0.0215
Mean consumption (units/week)		1.2463***	0.0029
IMD	IMD5 (least deprived)	Ref	
	IMD4	1.1851***	0.0436
	IMD3	1.2540***	0.0556
	IMD2	1.2730***	0.0668
	IMD1 (most deprived)	1.7310***	0.1120

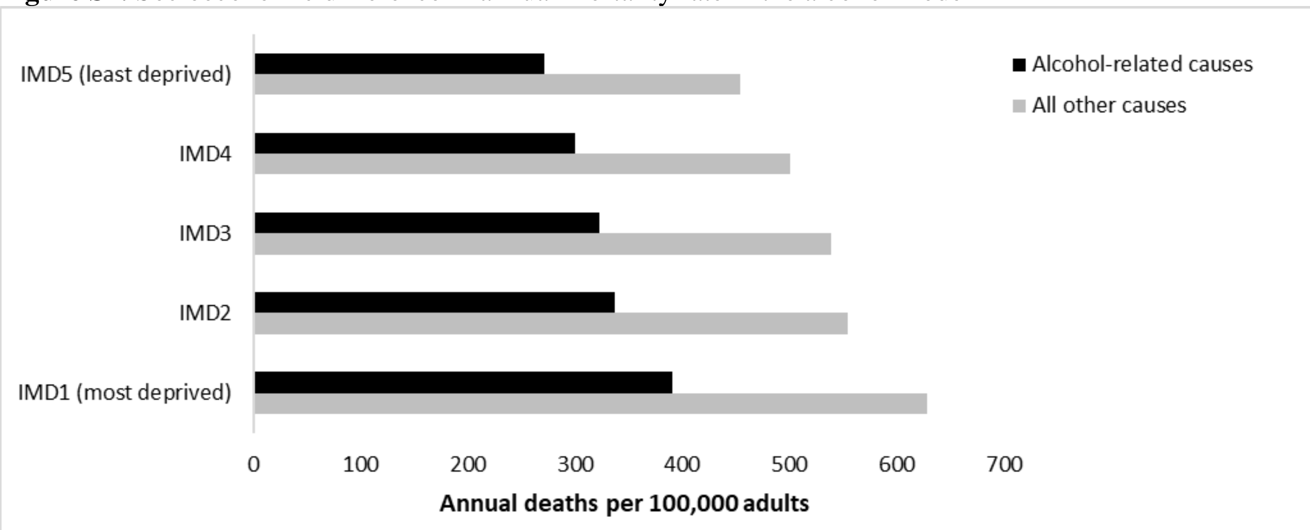
*p<0.05, **p<0.01, ***p<0.001
Source: Beard et al. 2015 (6)
IMD: Index of Multiple Deprivation

Figure S1. Socioeconomic difference in annual mortality risk for smokers



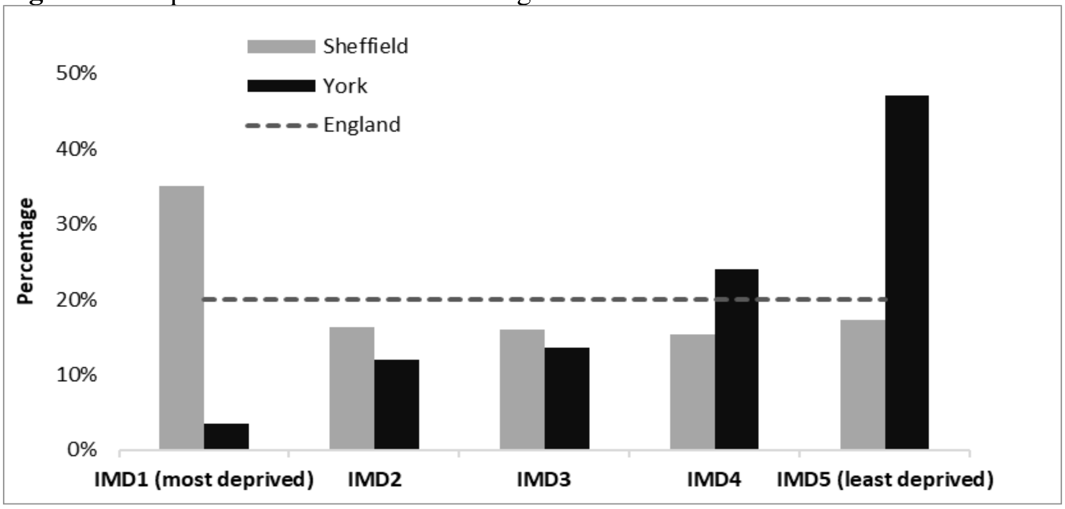
IMD: Index of Multiple Deprivation

Figure S2. Socioeconomic difference in annual mortality rate in the alcohol model*



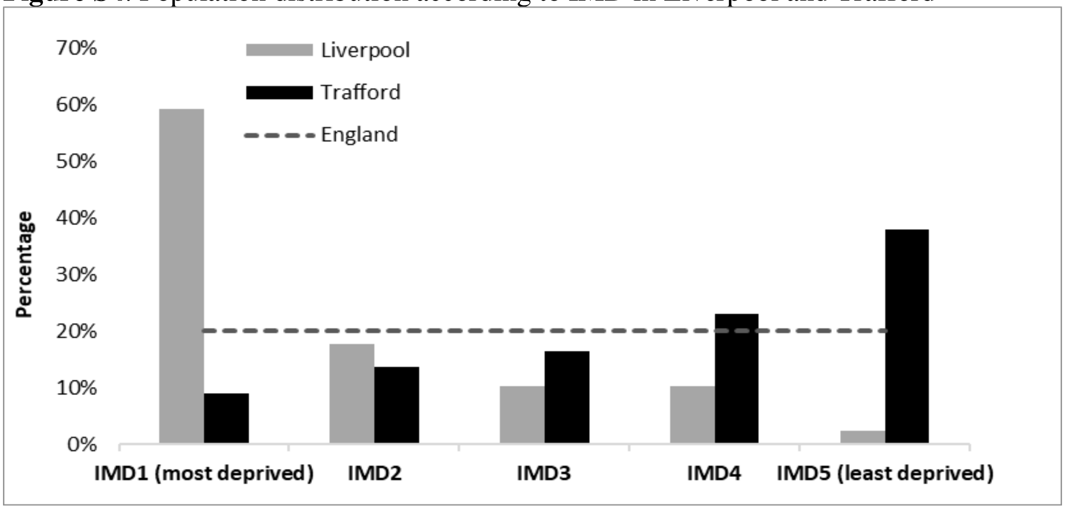
* extracted from Office for National Statistics (ONS) data 2012-2016
IMD: Index of Multiple Deprivation

Figure S3. Population distribution according to IMD in York and Sheffield



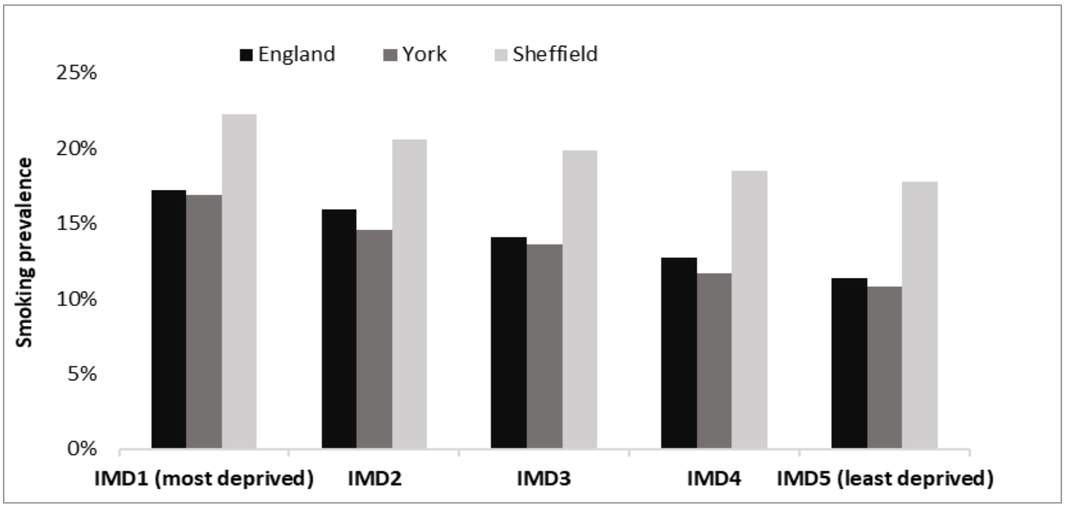
IMD: Index of Multiple Deprivation

Figure S4. Population distribution according to IMD in Liverpool and Trafford



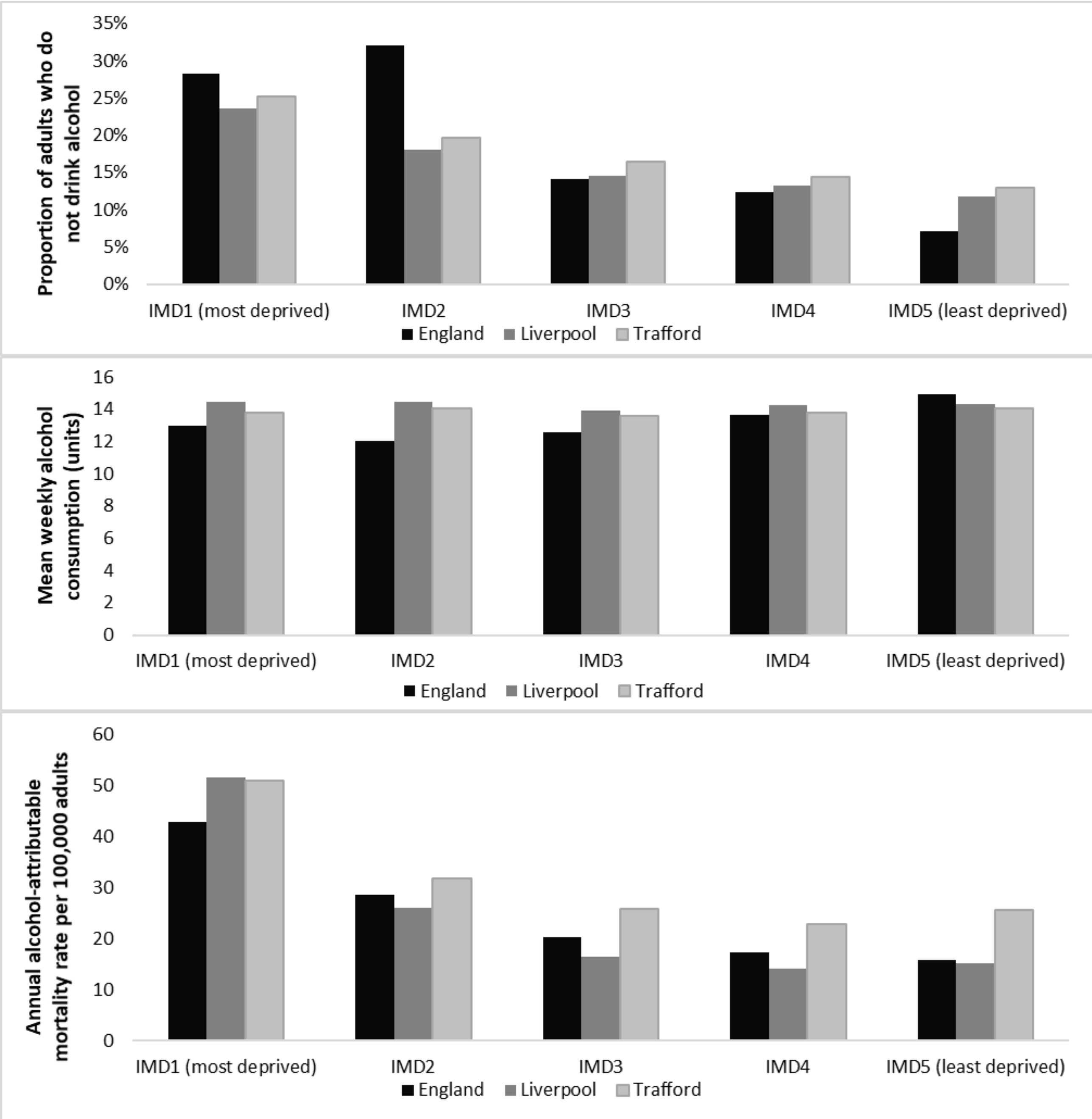
IMD: Index of Multiple Deprivation

Figure S5. Variation in socioeconomic difference in smoking prevalence for England, York and Sheffield



IMD: Index of Multiple Deprivation

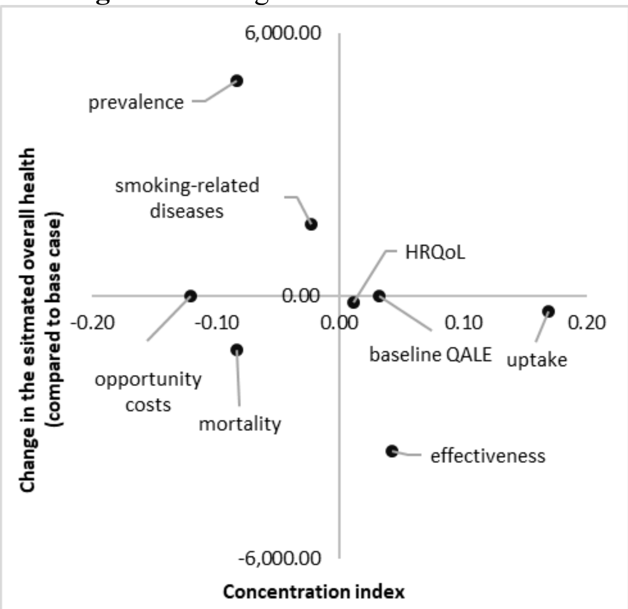
Figure S6. Variation in socioeconomic differences in model inputs for England, Liverpool and Trafford



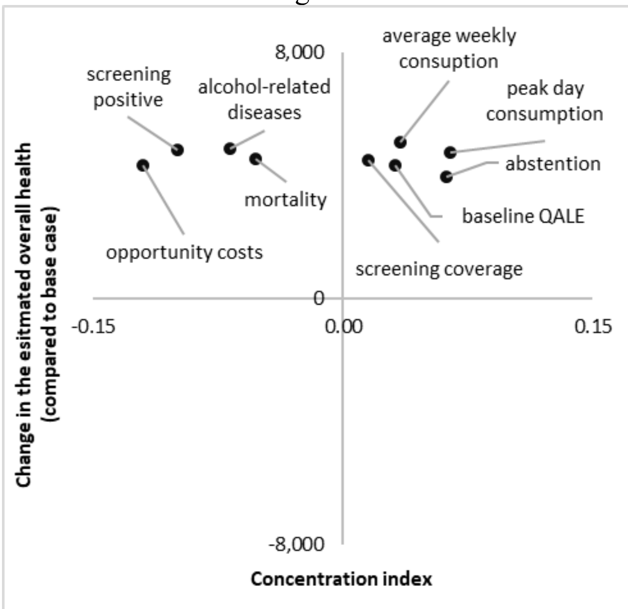
IMD: Index of Multiple Deprivation

Figure S7. Impact on overall health vs. concentration index where socioeconomic differences are ignored

Smoking model: e-cigarette vs 'no intervention'



Alcohol model: Next Registration vs 'no intervention'



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